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Shedding light on avoided disasters: Measuring the invisible benefits of disaster risk reduction using probabilistic counterfactual analysis

Authors

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Abstract

The goal of Disaster Risk Management (DRM) is to ensure that society continues to function, thrive, and recover quickly despite shocks arising from natural or human actions; to ensure, in short, that natural hazards do not become disasters. Success in the world of DRM means 'nothing happens,' but this poses a dilemma towards recognising and incentivising successful DRM interventions since they are made invisible by the very nature of their success. How then do we highlight and learn from successes if we do not see them? Likewise, how do we incentivise policymakers to make better risk-informed decisions when they are not credited for pro-active actions nor accountable for the consequences of doing nothing? This study discusses four types of situations where successful DRM interventions are made invisible: (i) success made invisible in the midst of broader disaster, (ii) success made invisible by nature of the success, (iii) success made invisible due to yet unrealised benefits, (iv) success made invisible due to the randomness of the specific outcome. We propose the use of probabilistic counterfactual analysis to calculate and highlight the 'probabilistic lives saved' from disaster risk management interventions, that would otherwise remain unnoticed. Two case-studies are provided, a school seismic retrofit program in Nepal and a cyclone evacuation effort in India. An important conclusion that emerges from these studies is that the value of risk reduction interventions should not be judged on the basis of specific outcomes, but on the basis of a broader exploration of potential outcomes. The shift in focus from realised outcome to counterfactual alternative provides a framework to identify and learn from successes in DRM, and reward individuals and institutions who have displayed political bravery in committing to the implementation of DRM measures despite invisible benefits.

Keywords: Probabilistic analysis; Counterfactual risk assessment; Risk communication; Risk perception

Contents

Introduction & Motivation

The goal of Disaster Risk Management (DRM) is to ensure that society continues to function, thrive, and recover quickly despite shocks arising from natural or human actions; to ensure, in short, that natural hazards do not become disasters. Disasters are “social in nature” — they stem not solely from the hazard, but from the interactions of the physical, built and social environments (Mileti, 1999). The extent of a disaster can be characterized by loss of life (Moore, 1958), as well as considerable damage and social, political and economic disruptions (Smith, 2005). DRM efforts try to ensure that such disaster elements are avoided (i.e. ‘nothing happens’), but this poses a dilemma for recognising and incentivising successful DRM interventions since they are made invisible by the very nature of their success. In addition, if the benefits of DRM actions manifest primarily as reduced impact when a hazard event occurs, these benefits may only be realised far in the future — particularly for rare and extreme events. Hence relying on the realisation of a disaster to evaluate mitigation efforts ignores the significant time delay between the investment in DRM and the hazard. When a large hazard event which ‘tests’ mitigation actions does occur, both news and research tend to focus on losses caused by the catastrophe, and very rarely is a past mitigation intervention revisited for analysis.

How then do we incentivise policymakers to make better risk-informed decisions when they are not credited for pro-active actions nor accountable for the consequences of doing nothing? There is a pressing need to develop better frameworks to judge the successes of DRM interventions, both to recognise and celebrate good decisions as well as to create incentives for further investment in mitigation. Literature suggests that celebration of past successes can benefit disaster risk reduction. For instance, inspirational visions can be key components of transformations to sustainability or resilience by helping communities articulate their values and desired futures (Wiek and Iwaniec, 2014). This can even help shape the very reality they forecast or explain. Focusing attention on these successes offers a novel way forward because it can help sustain and amplify efforts that already exist, and enable learning from positive examples rather than hyperfixation on the many negative ones which dominate the news and research literature (e.g. Leach et al., 2012). Shedding light on otherwise invisible benefits of successful DRM interventions is crucial to the achievement of large-scale transformations (Scott, 1998).

In this paper, we focus on four types of situations where successful DRM interventions are made invisible:

1) **Success made invisible in the midst of broader disaster.** Successful mitigation may result in fewer losses after a disaster, but this success is obscured amid the catastrophe and losses that were still incurred.
2) **Success made invisible by nature of the success.** A hazard becomes a disaster on account of the impacts it has on society. If mitigation efforts are so successful that there are no perceivable impacts, both the potential disaster and the successful mitigation are made invisible.
3) **Success made invisible due to yet unrealised benefits.** On account of the large time delay between the mitigation intervention and its benefits being realised, mitigation efforts could be seen as unsuccessful or unnecessary until a hazard event occurs.

4) **Success made invisible by the randomness of the specific outcome.** Hazards are stochastic processes, hence any single occurrence is only one of several possibilities that could have occurred. Recognising that the parameters of the event that actually occurred could easily have been different, successes can be made invisible if the hazard randomly does not strain mitigation measures, e.g. a near-miss.

To address these invisibilities, we develop and demonstrate a novel application of probabilistic counterfactual risk analysis to highlight and celebrate successful DRM interventions based on *counterfactual outcomes* rather than realised past outcomes or unrealised future outcomes. The systematic implementation of such analysis would enable us to (i) build a collection of case studies of past interventions that feature well-articulated, specific, implemented, and measured successes towards a safer, more resilient future, (ii) give a quantitative measure that focuses on celebrating benefits of intervention, independent of the specific occurrence of the hazard event against which the intervention was implemented, (iii) provide a means for crediting policymakers for sound decisions, even if the benefits of these decisions are not felt till much after decisions were taken, (iv) monitor progress in disaster risk reduction independent of the realised outcome of such interventions.

The potential stakeholders for this framework are multiple. Policy-makers (central and local governments) can be incentivized to invest more in risk reduction, by making visible to their constituents the benefits of such investments, even if these benefits are not realized. The framework would also enable disaster risk management practitioners to learn from positive lessons (rather than negative ones), which can be emulated in similar contexts. It can also serve donors as a means to evaluate projects and monitor progress, even if no tangible benefits are seen until a disaster strikes.

The paper is organised as follows. In Section 2, we draw on research on risk perception and social psychology, as well as the political aspects of disaster policy to highlight some of the challenges faced in evaluating disaster risk measures. This motivates our proposed framework of probabilistic counterfactual analysis. In Section 3, we introduce the framework in the context of DRM. Two case studies are used to illustrate the framework in Section 4: a school earthquake retrofitting program in Nepal and the evacuation of coastal communities in India prior to the landfall of a major cyclone. These showcase the different types of situations where successful DRM interventions are made invisible and the applicability of the method for different hazards. To provide further examples of where the method can be applied, we also provide a list of sample DRR measures. These include instances where successes are made invisible due to yet unrealised benefits, and cover different hazards as well as geographical regions. In Section 5, we discuss our results from our case studies as well as possible extensions and limitations. Finally, we conclude in Section 6 by summarising the work and its implications.

Risk perception and the invisibility of DRM

Even though effective mitigation of extreme events is both possible and already happening, there are many challenges faced in recognising and evaluating them.

If disaster risk management interventions are successful in their goal to eliminate or reduce the impacts of hazards on society, fewer people will experience the impacts of disasters. Research on risk perception has shown that people significantly underweigh low-probability events they do not have experience with (Tversky and Kahneman, 1973; Hertwig et al., 2004; Newell et al., 2016). This results in a strange paradox: the more mitigation efforts help successfully avoid disasters, the more we might underweight the risks posed by hazards and extreme events. This invisibility of mitigation successes is further exacerbated by the perception of disasters as the result of hazards that overwhelm societies - rare events, or “acts of god” for which it is impossible to prepare (Gaillard, 2019).

The field of social psychology provides further insight into why DRM evaluation is often so challenging. Research has shown that people’s emotional responses to events are influenced by their perception of “what might have been” (Medvec et al., 1995; Roese and Olson, 2014). A disaster event is a break from normalcy that triggers imaginations of alternative realities or *counterfactuals*: What if the disaster had never happened? What if it had hit a neighbouring town instead? In the aftermath of negative experiences, these counterfactuals are usually in an “upward” direction, where one imagines a better outcome than the realised outcome (Blix et al., 2016), e.g. thinking about the ways in which one could have avoided a car accident. Perceiving the benefits of mitigation, however, often requires comparing reality to a worse outcome or “downward counterfactual”, which is not a natural cognitive process, e.g. imagining a car accident happening on a routine trip to work. Further, counterfactuals are typically triggered by shock or surprise (Epstude and Roese, 2008; Kahneman, 1995). When a disaster has not happened yet or has been so successfully avoided that the hazard event is not perceived as a disaster, this “trigger” is missing.

Another challenge faced in recognising successful mitigation measures is that good DRM decisions are made invisible by the fact that they are evaluated only against the outcome that occurs instead of all possible events that could have occurred. The extreme case occurs when success has not been realised because the hazard has not occurred. As with many actions to mitigate climate change, DRM interventions require immediate sacrifice for seemingly uncertain benefits at a much later time (Weber, 2006). This time delay means that mitigation successes are rendered invisible until the eventual realisation of a hazard; excepting situations when mitigation measures also introduce co-benefits, which are a crucial part of effective DRM and which we discuss further in our conclusion.

Probabilistic counterfactual analysis addresses the aforementioned challenges faced in evaluating disaster risk measures. By accounting for alternative scenarios with their associated probabilities and explicitly identifying how a mitigation measure decreases the impact on society, it counters the natural cognitive perceptions which hinder the way people process risk and hence measure and evaluate mitigation successes. Since the framework can also be applied to measures for which success has not been realised to consider all possible future scenarios, it can quantify the long-term benefits of DRM decisions. It is essential that we invest in disaster mitigation, especially given the increasing frequency of disasters in the context of climate change (Jha et al., 2011). However, doing so in the light of the time delay between the intervention and its benefits combined with the invisibility of successful risk reduction means that decisions to invest in mitigation require remarkable political bravery. If these decisions are not recognised and rewarded, the interventions may be seen as ineffective or unnecessary with potentially disastrous consequences. Probabilistic counterfactual analysis provides a framework to rightly assess these difficult decisions.

Highlighting success in disaster risk management through counterfactual analysis

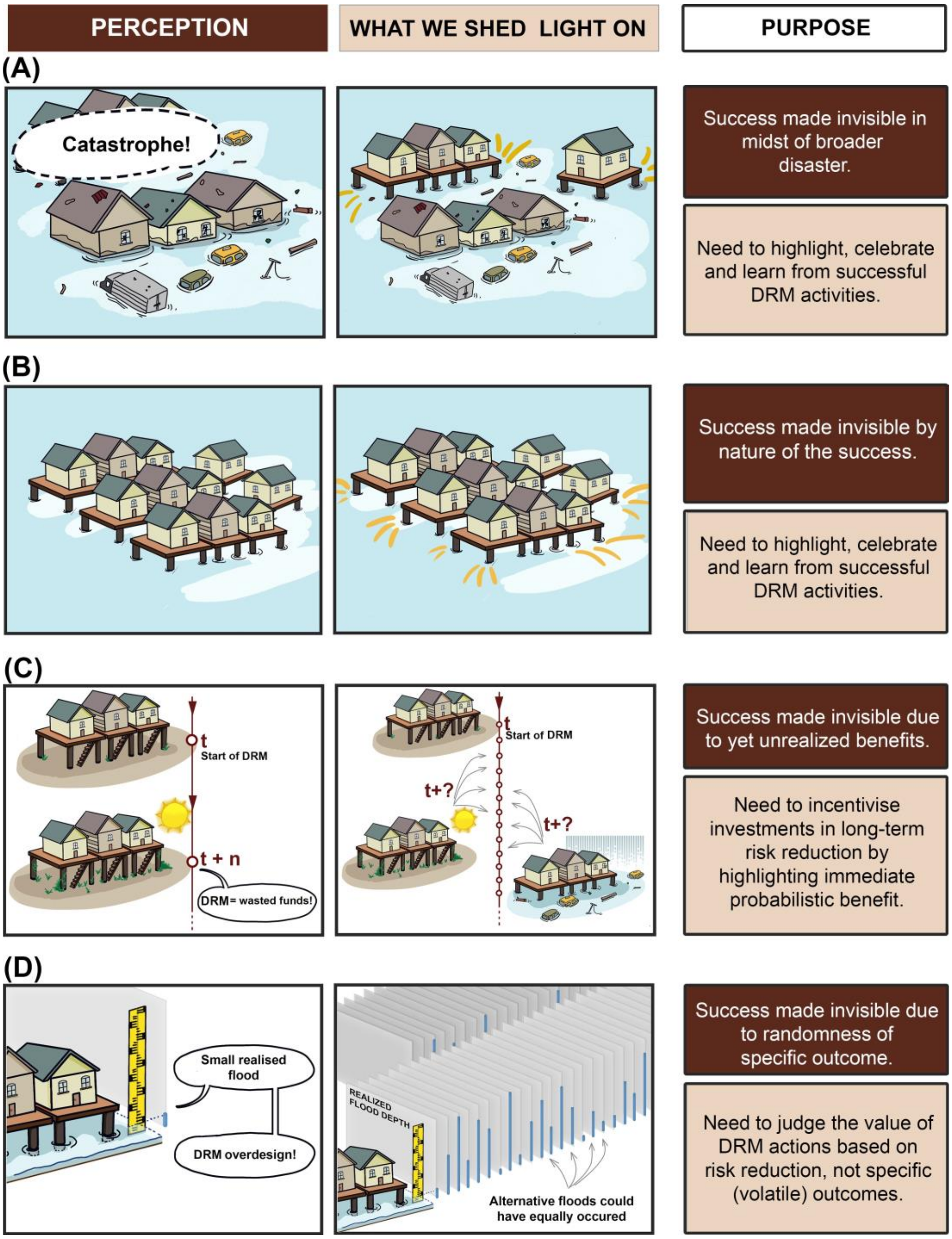
Counterfactual Analysis and DRM

The concept of counterfactual analysis is an old one. It is indeed closely linked to the analysis of causality theory in philosophy (Todorova, 2015), and often associated with 20th century theorising on "possible worlds" used in formal logic, philosophy, linguistics and more (Lewis, 2005). Counterfactual analysis typically starts with the creation of "what if..." scenarios, around which alternative branches of history can be explored. Combining counterfactual analysis with probabilistic methods, we can further constrain the scope of potential alternative branches of history by accounting for their relative probabilities based on best available data.

The idea that realised history is but one among many alternative "worlds" is a useful concept that supports our application of counterfactual analysis to shed light on invisible benefits of disaster risk management. Through this lens, in cases A and B of Figure 1 we shed light on *successes made invisible in the midst of broader disaster* and *successes made invisible by nature of their success* by comparing a past disaster (realised history) to an alternative world in which a particular DRM intervention was not implemented. In case C of Figure 1, we shed light on *successes made invisible due to yet unrealised benefits* by comparing a past with no hazard event (realised history) to alternative worlds where hazard events occurred according to their probability-magnitude characteristics (obtained from probabilistic hazard analysis). In case D of Figure 1, we shed light on *successes made invisible due to the randomness of specific outcomes* by comparing a past hazard event that had relatively small consequences (realised history) to alternative worlds representing the full spectrum of potential realisations of that hazard event. Each of these cases are examples of downward counterfactual analysis, where the alternative realisation is worse, to demonstrate the value of DRM interventions.

The use of counterfactual analysis has received growing attention in the disaster risk management field, though mostly to highlight failings in DRM rather than successes. Counterfactual analysis has been used to provide a way to capture the range of outcomes due to highly uncertain and random variables in a small but growing variety of applications including earthquakes (Woo and Mignan, 2018; Lin et al., 2020), climate change (Shepherd et al., 2018), terrorism and cyber security (Woo et al., 2017; Oughton et al., 2019), and volcanic eruptions (Aspinall and Woo, 2019). In previous applications, counterfactual exploration of alternative hazard events at different times of day, locations, or magnitude/intensity have shown that randomness plays a large role in the specific consequences of hazard events (Woo, 2019; Lin et al., 2020). Downward counterfactual risk analysis has been used primarily to point out worse potential outcomes for the purpose of insurance, preparedness, or future mitigation (e.g. Woo, 2019; Lin et al., 2020; Aspinall and Woo, 2019). We propose the use of downward counterfactual analysis to quantify improvements in resilience or celebrate past successes in DRM: this marks a fundamental shift in the application of counterfactuals in risk analysis. By focusing on celebration of past successes, this work presents a novel domain of application of counterfactual disaster risk analysis beyond highlighting potential worse outcomes and failures in DRM.

Figure 1. A schematic of invisibilities in mitigation successes using stilt houses as the mitigation and flooding as the hazard.



Counterfactual Analysis and Risk Analysis

Risk can be broadly defined as the likelihood of future undesired consequences produced from potentially damaging events such as natural hazards. The most common framework to quantify risk expresses it as a function of three distinct but interrelated

components (UNISDR, 2009): (A) Hazard, which refers to the likelihood of potential damaging events, (B) Exposure, which refers to the location and attributes of community assets such as people, buildings and infrastructure and (C) Vulnerability, which refers to the susceptibility of the exposure to sustain impact or harm for a given hazard intensity. Thus, risk can be seen as a function of a set of parameters that characterise each of the three components.

In the counterfactual analysis framework, the first step is to characterise the factual, realised event, around which counterfactuals can be defined and analysed (e.g. Lin et al., 2020). The impact resulting from the realised event should be characterised in terms of its relevant risk parameters:

$$Irealised \;=\; f\,(\theta_H, \theta_E, \theta_V)\;, (1)$$

where θ_H are the hazard parameters (e.g. magnitude of the event, its location, time etc.), θ_E are the exposure parameters (e.g. location of buildings and the number of people exposed), and θ_V are the vulnerability parameters (e.g. structural building characteristics, social vulnerability characteristics, etc.).

This then sets the basis for exploring alternatives where a single or multiple of the risk parameters are modified in order to define a new, *counterfactual* event:

$$I_{counterfactual} \;=\; f\,(\theta_H + \delta_H, \theta_E + \delta_E, \theta_V + \delta_V)\;, (2)$$

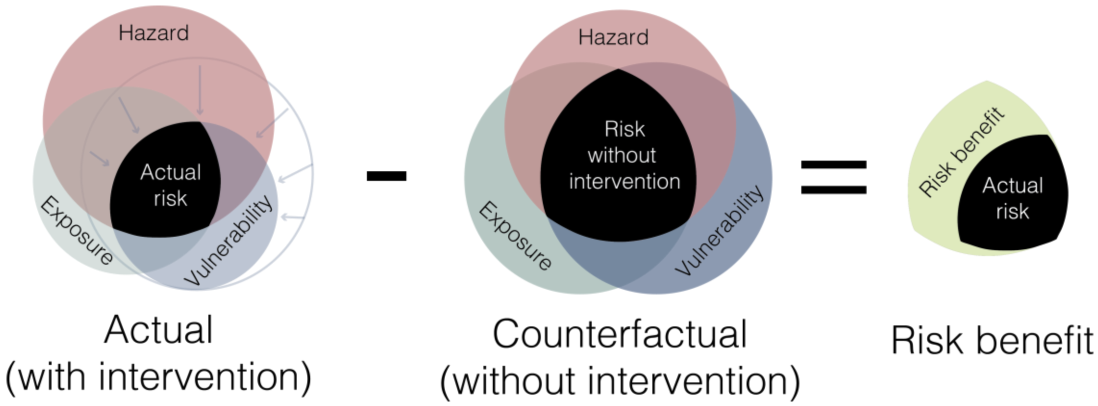
where $\delta_.$ are the variations over one or many of the parameters that defined the original past event.

In most situations, we will treat the factual realised event as deterministic, where all parameters $\theta_H, \theta_E, \theta_V$ are known and fixed. Alternatively, we may want to treat some parameters as fixed and some as unknown. However, it is often useful to explore a broad range of counterfactual events, accounting for their relative probabilities. This is then an application of the risk analysis framework to counterfactual analysis. In this setting, some of the parameters in equation 2 are unknown, but with known probability distributions (e.g. frequency-magnitude curves of earthquake occurrence). The probability of each counterfactual alternative is then associated with the joint-probability of unknown parameters. In practice this rarely has an analytical formulation, and is calculated by means of simulation (e.g. Monte-Carlo simulation).

Comparing the realised event (fixed or probabilistic) to the distribution of counterfactual events enables us to quantify the benefits (*B*) of positive actions towards risk mitigation (see equation 3 and Figure 2).

$$B \;=\; I - I_{counterfactual} \qquad (3)$$

Figure 2: Conceptual diagram of the counterfactual risk analysis framework.



In our demonstration, we measure the benefits of DRM intervention in terms of *probabilistic lives saved*. Indeed, the reduction of mortality is the first target indicator within the Sendai Framework For Disaster Risk Reduction (UNISDR, 2015), reflecting the primary goal of global DRM practice to save lives. We also note that our approach is similar to the measure of 'years of life saved' by medical interventions that is calculated systematically in the field of public health (Tengs et al., 1995). Similar analysis could be conducted for measuring reduced losses in financial terms, as is often the case in cost-benefit analysis, though these analyses have the tendency to highlight "successful" DRM interventions as those that protect high-value areas rather than high-vulnerability areas, often exacerbating inequities (Markhvida et al., 2020; Lallemant et al., 2020).

Case studies – Celebrating success

We illustrate the use of probabilistic counterfactual analysis to highlight invisible benefits of DRM, and also to demonstrate its capability to adapt to a wide range of hazards and DRM interventions. The two case studies in this section were chosen as they exemplify three of the invisibilities highlighted in the paper, cover two major hazards, and two very different types of DRM interventions (structural upgrading and early-warning respectively). The first case study focuses on a school earthquake retrofitting program in Nepal. It illustrates Case A of Figure 1, where a very successful risk reduction program was made invisible amid the tragedy of a broader catastrophe. The second case study focuses on the evacuation of coastal communities in India prior to a major cyclone making landfall. It illustrates Case B and D of Figure 1, where the benefits of the massive evacuation is made invisible by nature of it having been so successful (i.e. news focuses on perceivable losses thus rarely highlights avoided disaster), and partially obscured by the lesser severity of the actualised hazard compared to that expected at the time. Finally, we finish this section by presenting a list of DRM interventions that fit Case C in Figure 1 - interventions with invisible successes due to yet unrealized benefits. This illustrates the diversity, creativity and broad geographic coverage of important DRM interventions which deserve to be highlighted, analysed and learned from.

Seismic retrofit of schools in Nepal

Event description

On Saturday, April 25, 2015 at 11:56am local time, a Mw 7.8 earthquake occurred about 80 km northwest of Kathmandu, the capital of Nepal (Hayes et al., 2017). It was followed by numerous aftershocks (Goda et al., 2015; Prakash et al., 2016). According to the Post-Disaster Needs Assessment, the Nepal earthquake resulted in 8,790 casualties, 22,300 injuries, and over 8 million impacted persons (about one-third of the population of Nepal) in 31 districts, resulting in an estimated 7 billion U.S. dollars of direct economic losses (Nepal NPC, 2015). In the education sector, 8,242 public schools were affected, including 25,134 fully destroyed classrooms and 22,097 partially damaged (Nepal NPC, 2015).

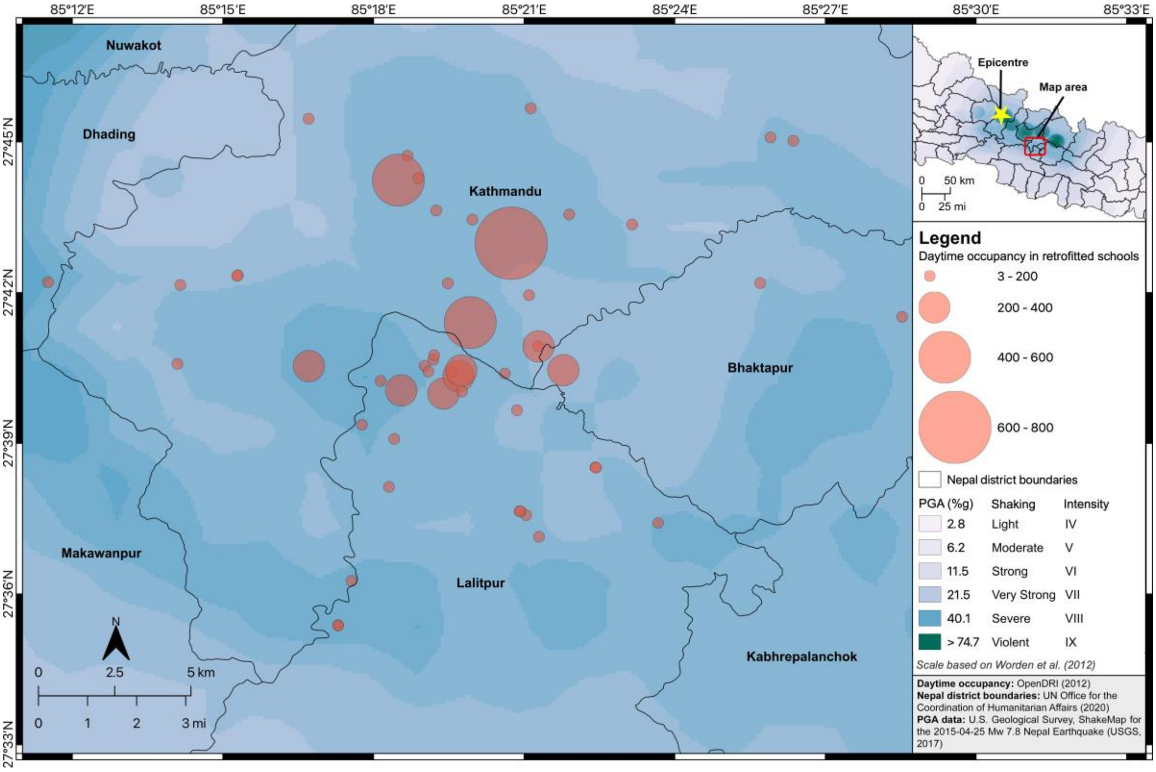
Before the event, the risk of such a large earthquake in the region is well known. It has been hypothesised that the recurrence interval of a “great Himalayan earthquake” (Mw > 8.0) is between 750 ± 140 and 870 ± 350 years on average in the east Nepal region (Bollinger et al., 2014). At the location of the 2015 earthquake, the last major earthquake was in 1344. And since the last destructive Nepal earthquake in 1934, studies have hinted strain buildup towards Kathmandu (Goda et al., 2015; Prakash et al., 2016).

DRM intervention

Amidst Nepal’s high seismic hazard and predominance of vulnerable non-engineered building construction (BCPR, 2004; Rodrigues et al., 2018), Government of Nepal recognized the need for earthquake-safe construction to reduce school vulnerability. In this work, we highlight the number of lives saved by the timely intervention of the School Earthquake Safety Program (SESP), a school retrofit program initiated in 1997 by the National Society for Earthquake Technology (NSET) and continued through the Nepal Safer Schools Projects (NSSP) by the Department of Education (Marasini, 2019). Prior to the earthquake, NSET reported that a majority of public schools were built via construction techniques using unsafe materials such as non-reinforced adobe, stone rubble in mud mortar, and brick in mud mortar (NSET, 2000). The safety of Nepal’s public school buildings is particularly important, as they serve as emergency shelters, housing tents and sites for medical services (Dixit et al., 2014). Furthermore, the collapse of a school building can cause intense psychological impacts to community members and especially children, and the return to school for students provides a sense of normalcy after a disaster (Dixit et al., 2014).

The primary aim of the School Earthquake Safety Program was to raise earthquake safety awareness in Nepal through outreach and capacity building amongst teachers, students, and parents, and to strengthen school buildings through seismic retrofitting by local masons (NSET, 2012). The first seismically retrofitted school was completed in 1999. By the time of the Nepal earthquake in April 2015, 300 schools were retrofitted, 160 of which were in the most affected districts. Among the 160 retrofit schools in the affected districts, 125 reported no damage, with 35 only reporting hairline cracks on plaster. Notably, none of the retrofitted schools collapsed or needed major repairs (Marasini, 2019). Our dataset shown in Figure 4 contained information on 70 of the 300 retrofitted schools (OpenDRI, 2012).

Figure 3. For each of the 70 retrofitted school buildings shown as circles on the map, PGA (in %g) are extracted as hazard input, and the daytime occupancy (represented by the size of the circles) are used to estimate the probabilistic fatalities. The dataset also contains physical characteristics that indicate potential for collapse (e.g. construction typology, number of stories, fragility curves).



Probabilistic counterfactual analysis

The downward counterfactual analysis is applied through a probabilistic approach to estimate building collapse for two scenarios: (1) the realised case where all 70 school buildings of interest were retrofitted, and (2) a counterfactual case where the school buildings are not retrofitted. For each school, we estimate the probability of exceeding a collapse damage state based on the following modelling parameters:

1) Earthquake hazard in terms of peak ground accelerations (PGA) generated using the USGS Global ShakeMap system (Wald and Allen, 2007),

2) School building characteristics including location, daytime occupancy, number of stories, and construction typology (OpenDRI, 2012)

3) Fragility curves describing the probability of collapse given the earthquake shaking intensity and construction typology. For the unretrofitted schools,collapse fragility curves were adopted from a study on earthquake mitigation in Kathmandu Valley before the Nepal Earthquake (JICA and MOHA, 2002). For retrofitted schools, we assumed a collapse fragility curve for a specially designed RC building from the same JICA and MOHA (2002) study. For the complete values of the fragility curves as two-parameter lognormal distribution functions, for all 70 schools in the analysis, see Rabonza et al. (2020).

We then implemented a Monte Carlo simulation, generating 30,000 realisations of Bernoulli trials of collapse based on the estimated collapse exceedance probabilities (probability of collapse for each building at the ground motion intensity estimated from the 2015 earthquake). To obtain a distribution of probabilistic fatalities, we obtained school building occupancy data (OpenDRI, 2012) and assumed a 20% fatality rate consistent with NSET's calculations for masonry and reinforced concrete buildings (Coburn and Spence, 2002; NSET, 2000). For the first scenario, the realised case, we use fragility curves to estimate collapse probability exceedance corresponding to a retrofitted building, whereas for the second scenario, we assume that the whole building stock consists of unretrofitted buildings and use unretrofitted fragility curves. For a complete description of the modelling parameters, see (Rabonza et al., 2020).

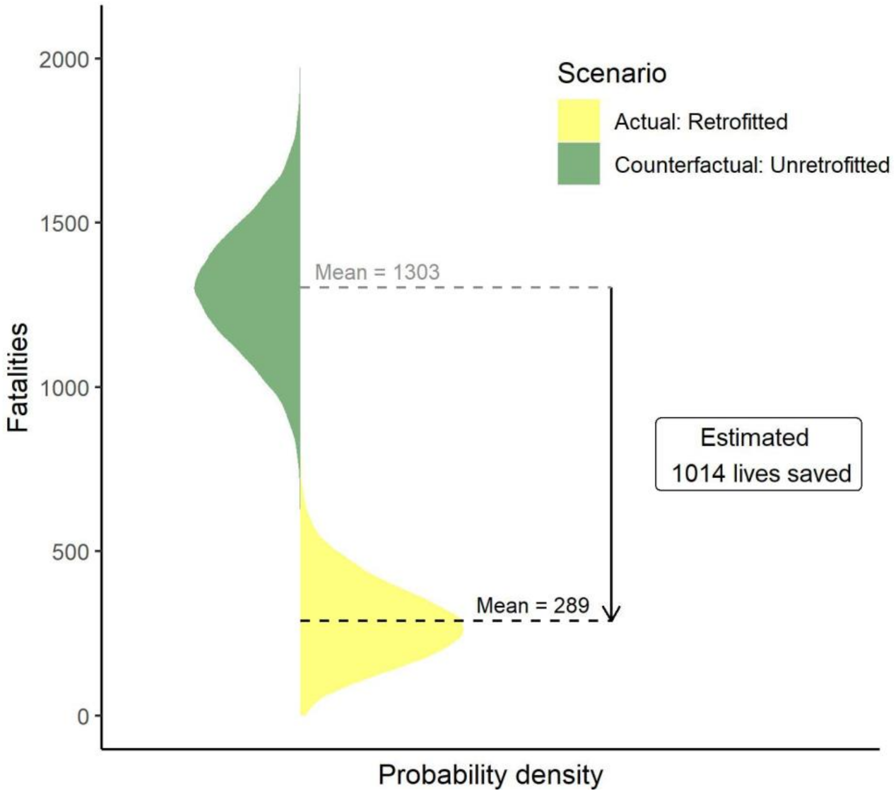
Results

The results of the counterfactual analysis show that the retrofit program saved hundreds of lives. In the realised scenario of retrofitted buildings, 7 out of the 70 school buildings on average were predicted to collapse (10% collapse rate), whereas for the counterfactual case, 33 out of the 70 school buildings were predicted to collapse on average (47% collapse rate). Figure 4 shows the distribution of fatalities due to collapsed school buildings in both scenarios.

Based on the analysis of the counterfactual Nepal earthquake without the risk reduction intervention, we estimate that the lives of approximately 1014 students and teachers were saved in Kathmandu by the retrofit of just these 70 schools in this single event. This was obtained by comparing the estimated mean casualties (n = 289) for the realised retrofitted case, shown in yellow, and the much higher mean casualties (n = 1303) for the counterfactual unretrofitted case, shown in green. We note that the actual reported number of casualties in the 70 retrofitted schools is unknown, and likely much lower still than our prediction, since no retrofitted schools collapsed. This is likely due to better performance of school buildings than modelled according to their fragility curves. Hence the number of lives saved may be conservative.

This case study highlights the invisible success of the SESP program amidst the 2015 Nepal earthquake,and illustrates how the counterfactual probabilistic analysis can be applied to celebrate previously invisible benefits in the context of a past disaster.

Figure 4: Relative number of lives saved due to the school retrofit policy implemented in Nepal before the 2015 earthquake. Estimated fatalities for the realised retrofitted case and the counterfactual, unretrofitted case, where 70 school buildings were not retrofitted prior to the 2015 earthquake. Fatality estimates are based on 30,000 simulations and show an average of 1014 lives saved, calculated as the difference in the average number of fatalities for both cases.



Cyclone evacuation in India

Event description

'Extremely Severe Cyclonic Storm' Fani hit the East Indian coast of Odisha on May 3rd 2019. With a maximum sustained surface wind speed of 204km/h, (RSMC New Delhi, 2019), it was the strongest tropical cyclone to strike the region since the 1999 Odisha super cyclone (WMO, 2019).

Cyclone Fani left an official count of 89 fatalities in India and Bangladesh, 64 of them in the East Indian state of Odisha. Of the 64 deaths, 51 are extreme wind-related fatalities (i.e. crushed by uprooted trees, collapsed walls and roof) (News18 India, 2019; UNICEF, 2019). The state bore the brunt of the human and economic impact of the cyclone, with approximately 16.5 million people in over 18,388 villages affected and approximately 362,000 houses experiencing catastrophic damage. Total damage and losses in the state was estimated to be 3.5 billion U.S. dollars (Government of Odisha, 2019; Mishra and Ojha, 2020).

DRM intervention

Despite the considerable impact on human lives and property, the damage caused by Cyclone Fani was small in comparison to the Odisha super cyclone of 1999, which resulted in approximately 10,000 fatalities and 4.5 billion U.S. dollars of damage (Kalsi, 2006). The reduced human and economic losses was partly a result of the fact that the observed peak storm surge height of 1.5m (RSMC New Delhi, 2019), was much below the 4m peak predicted (ECHO, 2019), as well as the 6.7m peak of the 1999 cyclone (Kalsi, 2006). At the same time, loss of life was also much reduced as a result of large-scale evacuation efforts taken by the government of Odisha, who evacuated approximately 1.55 million people towards 9,177 shelters before the cyclone's landfall. In contrast, at the time of the 1999 super cyclone, Odisha state only had 23 cyclone shelters for evacuation (IFRC, 2001).

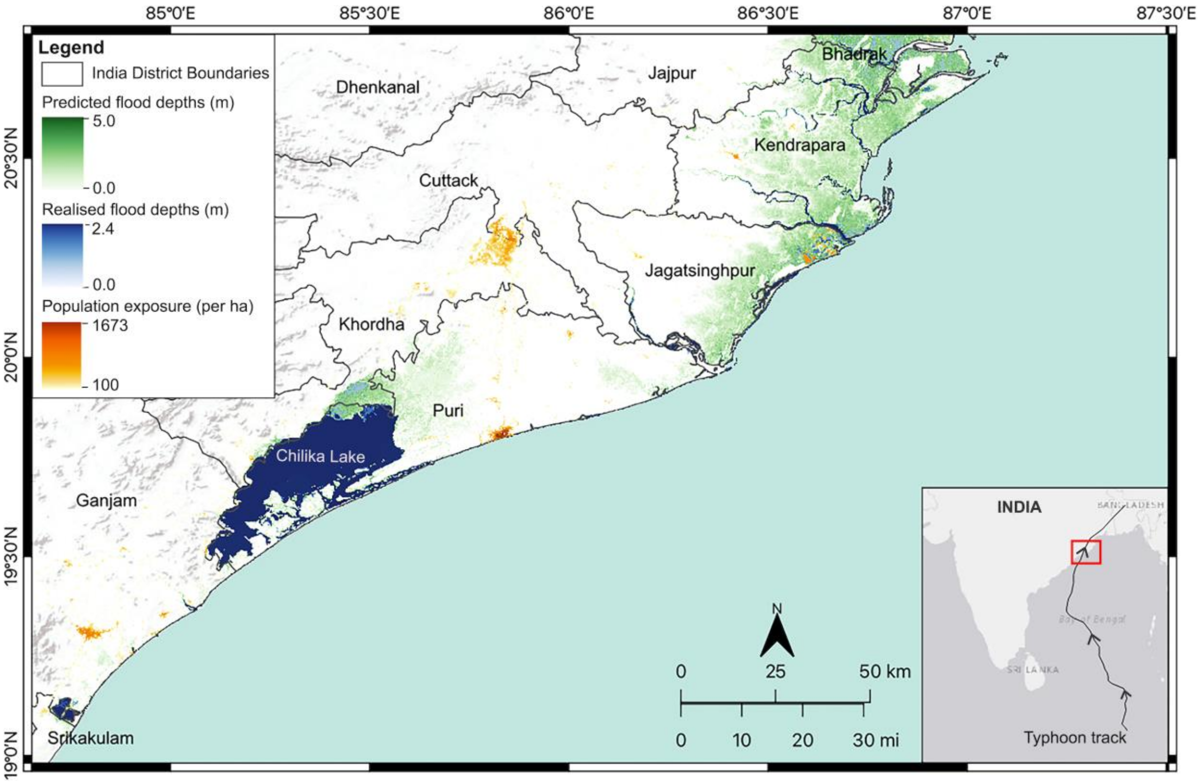
Probabilistic counterfactual analysis

We calculate probabilistic lives saved as a result of the evacuation during Cyclone Fani through two counterfactual scenarios. We modelled the outcome of the *realised flood event without the realised evacuation efforts*, in comparison to the realised evacuation scenario. This is an example of Case B from Figure 1, where we highlight the success of the evacuation which otherwise went unnoticed by nature of its success. We also modelled the counterfactual realisations of Cyclone Fani with higher storm surge as originally predicted before the cyclone's landfall, also without evacuation efforts. This represents the family of *expected* cyclone surges given what was known at the time, and against which the mass evacuation decision was made. This then is an example of Case D from Figure 1, where we highlight the success of the evacuation made invisible by the randomness of the hazard.

Counterfactual realisations of storm surge were used to generate flood maps using the bathtub flood method (Yunus et al., 2016), and accounting for local tides, surge heights (GDACS, 2019) and elevation (Yamazaki et al., 2017). We used a tide level of 1.5m which corresponds to the average monthly high tide in Puri (Meteo365, 2021). Exposed population was derived from gridded population density data (WorldPop, 2021), downscaled with higher resolution World Settlement Footprint map (Marconcini et al., 2020). The result is a detailed 10m resolution population density map for the area. A flood fatality model was used to estimate fatality rate as a function of water depth, as per the cumulative lognormal distribution model by Jonkman (Jonkman, 2007):

$$F_D(h) = \Phi\left(\frac{(\ln h) - 7.6}{2.75}\right)$$

Figure 5. Modelled flood depths for the predicted and realised cyclone flood event with the population exposure per hectare. The predicted event uses a 3.6m storm surge.



A limitation of the approach is the high uncertainty in both the fatality model and the initial storm surge height. To take these uncertainties into account, Monte Carlo analysis was performed to simulate different storm surge heights and different parameters of the fatality function. The storm surge height was sampled from a normal distribution with a mean of 3.6m and standard deviation of 1.1m, matching the range of estimates before the cyclone made landfall (Mohanty, 2019; ECHO, 2019). The mean parameter of the fatality model was likewise treated as uncertain and normally distributed with standard deviation of 1m. Figure 5 shows the modelled flood depths and population exposure per hectare with both the realised and predicted storm surge heights.

We make note that the model only accounts for fatalities resulting from flooding, and therefore excludes those caused by winds. This is because the majority of cyclone fatalities in high-fatality cyclonic events are a result of floods, as was the case in the 1999 super cyclone (Kalsi, 2006). However, it should be noted that this limitation would lead to an underestimation of fatalities in our models.

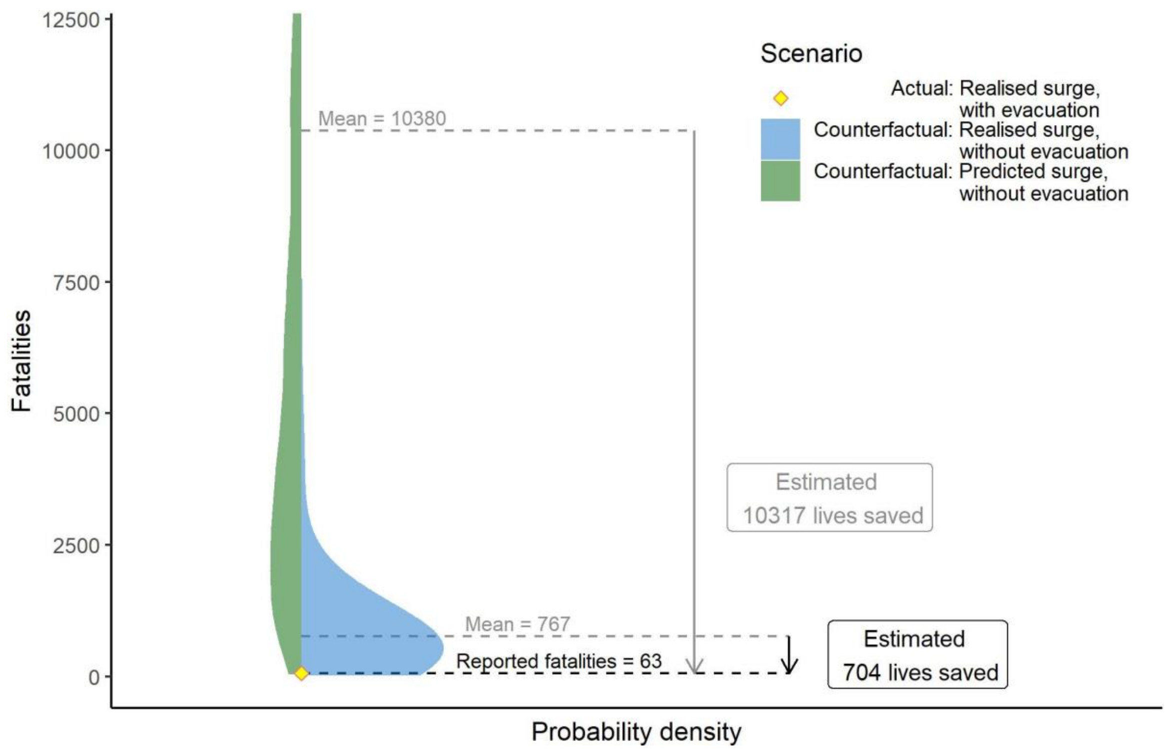
We note that the storm surge level of 1.5 meters is in the same order of magnitude as the vertical uncertainty in the DEM. This is a common limitation for flood modelling with global data and the Multi-Error-Removed Improved-Terrain DEM we applied was specifically made to reduce this issue (Yamazaki et al., 2017). The results remain uncertain, and are therefore to be used for illustrative purposes. Higher resolution DEM, tidal, exposure and fatality models would improve the counterfactual predictions.

Results

In reality, Cyclone Fani caused 63 fatalities. The first counterfactual scenario, using the realised surge height but counterfactual absence of evacuation, would have led to an estimated 767 fatalities (mean = 767, Interquartile range = 240 - 970). The second counterfactual scenario, using the counterfactual storm surge that was expected prior to landfall and absence of evacuation, would have led to an estimated 10380 fatalities (mean = 10380, Interquartile range = 2750 - 13200). Figure 6 shows the distribution of fatalities as a result of flooding in both scenarios.

The first counterfactual scenario highlights the benefits of life-saving interventions in a realised hazard event in this case, the evacuation efforts during Cyclone Fani. The second counterfactual scenario highlights the fact that the full benefits of the evacuation efforts may have been partially obscured by the lesser severity of the realised hazard.

Figure 6. Estimated fatalities for actual and counterfactual cases. The counterfactual cases correspond to the realised storm surge with no evacuation, as well as the expected storm surge (against which the evacuation plan was made) with no evacuation. The estimates are based on 250 and 1,350 simulations respectively.



Through this lens, it can be seen that the effective evacuation of coastal communities preceding Cyclone Fani is associated with an estimated 704 lives saved in the realised storm surge event, and 10317 lives saved in the predicted storm surge event.

This scenario thus highlights the usefulness of our model in drawing attention to potential 'invisible' benefits of risk reduction interventions, some of which may otherwise not be fully realised or acknowledged after a hazard event with a lower-than-expected severity. In doing so, it further highlights how our models may allow us to better monitor progress in disaster risk reduction independent of the realised outcome of such interventions.

Success made invisible due to yet unrealised benefits

The two case studies illustrate the use of counterfactual probabilistic risk analysis to highlight the lives saved by DRM measures. While these are in the context of earthquakes and floods, the methodology can be adapted for a wide range of hazards and measures. In Table 1, we present a list of DRM interventions implemented in various regions of the world. This is a small reflection of the diversity of measures which should be analysed, celebrated and shared even if their benefits have yet to be realised. Each intervention targets one or more risk components, which can help define the counterfactual scenarios required for evaluation.

Measuring probabilistic lives saved as a result of an intervention should become standard practice in the DRM field. The shift in focus from specific outcome to *probabilistic lives saved* offers a framework to reward individuals and institutions who have displayed political bravery in committing to the implementation of DRM measures despite time delay in the realisation of its benefits, lack of follow up risk auditing and other challenges. This simple gesture can motivate further good work.

Table 1. Table of example disaster risk reduction measures (DRR) for which counterfactual risk analysis can be applied for evaluation. The risk components affected are coded as H for hazard, E for exposure and V for vulnerability.

DRR Measure	Risk Component	Example
Earthquake		
Reconstruction and retrofit	V	In San Francisco, a mandatory retrofit program for older, wood-framed multi-family buildings with soft-story conditions was created in 2013 (SFDBI, 2021).
Construction inspection	V	In Turkey, the 2001 Construction Inspection Law led to better building quality control (Gunes, 2015).
Public awareness	E, V	In Kyrgyzstan, the safe evacuation of 32 children from summer camp after the 2011 M6.1 earthquake was attributed to preparedness exercises (ECHO, 2013).
Flood		
Urban planning	V	In China, the ‘Sponge City’ concept was established in 2014 to promote filtration and storage of stormwater in highly urbanized areas (Chan et al., 2018).
Flood management infrastructure	E	In the Philippines, a polder wall for protecting the Valenzuela-Obando-Meycauayan (VOM) area was constructe in 2014 (JICA, 2018).
	H	In Netherlands, the Delta Works programme was implemented between 1954 and 1997 to construct dams and other flood protection infrastructure (Kind, 2014).
Emergency response	V	In Gambia, integration of DRR interventions in emergency response proved its worth during the 2012 floods (ECHO, 2013).
Typhoon/Tropical Storm		
Public awareness	E, V	In the Philippines, explanations from barangay officials on the deadliness of storm surges led to a successful preemptive evacuation on Manicani Island implemented two days before Typhoon Haiyan hit. As a result, only one out of more than 3000 residents died (Canoy, 2013; Lagmay et al., 2015).
Early warning system	E	In Bangladesh, a Doppler Radar system, which gave timely warning, was partly credited for the lower than expected casualty count of 190 during Cyclone Aila in 2009 (Izumi et al., 2019).

Storm risk management	E, V	In Myanmar, cyclone shelters provided refuge during Cyclone Mahasen in 2013, their year of completion (JICS, 2013).
Landslide/Avalanche		
Early warning system	E	In Bolivia, no victims were reported after the 2011 mega landslide due to the evacuation effort informed by a geodynamic hazard monitoring system (ECHO, 2013).
Mitigation infrastructure	E, V	In Tajikistan, a 120m long mudflow channel was rehabilitated to protect a village of 1760 inhabitants (UNDRR, 2006).
Tsunami		
Public awareness	E, V	In Indonesia, disaster risk education was provided in schools around Ciletuh-Palabuhanratu UNESCO Globa Geopark (Muslim et al., 2019)
Fire/Drought		
Early warning system	E	In Lebanon, a wildfire forecast system using dynamic weather forecasts was launched in 2016 (Mitri et al., 2017).
Irrigation	H, E, V	In Malaysia, irrigation recycling which begun in 1970 saved more than 3000ha of crop in the 2015-16 drought (JICA, 2018).

Discussion

The Nepal 2015 earthquake case shows that even in the midst of a tragic disaster, there are often successes to celebrate that prevented many more lives from being lost. Our counterfactual analysis demonstrated that the successful earthquake retrofit of 300 school buildings as part of the government-led School Earthquake Safety Program saved hundreds of probabilistic lives. The benefits of the retrofitting program were even further obscured since the earthquake occurred on a Saturday while school sessions were off (luckily!).

The 2019 Cyclone Fani made landfall on the Indian coast without leading to the major disaster feared. This was the result of the evacuation of 1.55 million people, and the fact that the predicted extreme storm surge didn't occur. The result was that 'only' 64 fatalities occurred in the case study area (UNICEF, 2019), the majority of them wind fatalities (News18 India, 2019). This is relatively few compared to similarly severe cyclones in the region. We applied our probabilistic counterfactual analysis to look at what would have happened without evacuation and what would have happened if the predicted storm surge had occurred. We found that the evacuation probably saved hundreds of lives and if the predicted storm surge had occurred the lives saved could have reached in the thousands to even ten thousands. This counterfactual analysis shows that the evacuation was necessary, successful, and presents important lessons for other regions and countries impacted by tropical storm hazards.

The case studies utilise first order risk analyses and contain numerous modelling uncertainties. The studies are therefore intended to serve as demonstration of the probabilistic downward counterfactual analysis approach, but the specific results and estimated lives saved have significant uncertainty, as demonstrated by the wide distributions of simulations shown in Figure 4 and Figure 6.

The case studies focus only on loss of life reduction. Other metrics of successful DRM interventions include reducing injuries, number of affected or displaced people, building damage, business interruption, livelihood losses, damage to cultural heritage, psychological distress and much more. Probabilistic downward counterfactual analysis can be applied equally for these alternative metrics.

Furthermore, it is becoming increasingly recognised that the benefits of DRM activities can go beyond impact reduction and loss-avoidance, and in fact should be designed as such. For instance, the reduction of background risk encourages positive risk taking (e.g., investment in productive assets, entrepreneurial activities), enables long term financial planning (e.g., to build up savings), and potentially increases the value of protected lands (Tanner et al., 2015). Investments in multi-purpose disaster risk reduction measures can also yield benefits that are unrelated to the reduction of background risks. These co-benefits can be economic (e.g., increased agriculture productivity with improved irrigation for drought management), political (e.g., improved governance through strengthening the disaster risk management capacity of civil society), social (e.g. increased parks and green leisure areas), and/or environmental (e.g., carbon sequestration, sediment and nutrient retention from protection or afforestation of wetlands). The nature and level of these co-benefits depend on the design of the disaster risk reduction measure (Tanner et al., 2015).

Conclusions

The field of disaster risk management faces the challenge of its failures being catastrophic while its successes go unnoticed. This makes it difficult to identify, celebrate, and spread positive lessons learned that could be emulated elsewhere, or to incentivise proactive decision-making on the basis of recognised successes. We have identified four types of situations where successful DRM interventions are made invisible: (i) success made invisible in the midst of broader disaster, (ii) success made invisible by nature of the success, (iii) success made invisible due to yet unrealised benefits, (iv) success made invisible due to randomness of specific outcome.

We propose and demonstrate the use of probabilistic downward counterfactual analysis to shed light on these otherwise invisible successes. Downward counterfactual analysis is the counter-intuitive process of understanding how a realised event could have been worse, as a way to highlight the benefits of an intervention. This application goes beyond the existing uses of counterfactual risk analysis that focus on pointing out worse potential outcomes for the purpose of insurance, preparedness, future mitigation and learnings from failures in DRM.

We further use the risk analysis framework to ascribe estimated probabilities to the simulated counterfactuals. The estimated probabilities constrain the counterfactual exploration to realistic scenarios. As in all risk analyses, the process requires scrutiny and transparency in the assumptions, data and analysis conducted. Doing so aims to avoid both misuse of the counterfactual framework and misrepresentation of the benefits of DRM. An example of misuse would be inflating the benefits of a DRM intervention by cherry-picking ‘ideal’ counterfactuals e.g. a hazard scenario too extreme and unrepresentative of the current knowledge of the hazard that the calculated lives saved would inflate.

An important concept that emerges from this study is that the value of a risk reduction intervention should not be judged on the basis of specific outcomes, but also on the basis of a broader exploration of potential outcomes. The same *good decision* may seem like overkill against a specific outcome, or may seem completely insufficient judged against another. Especially in a field focused on long-term resilience and often rare (therefore volatile) events, *realised outcomes* bias our perceptions and judgements. This is also relevant to the monitoring of risk reduction targets, including those of the Sendai Framework (UNISDR, 2015). Mortality on any given year, or specific place, may not reflect adequate or inadequate disaster planning, but rather chance outcomes. Encouraging long-term resilience, which may not ‘pay-off’ for decades (e.g. for climate-adaptation), will therefore require a shift in focus from realised outcome to unrealised risk reduction.

The innumerable successful DRM interventions implemented in communities worldwide (e.g. in Table 1) represent a critical data-set to learn from, adapt, share and implement such activities where they are further needed. This is only possible if these successes are identified, analysed and celebrated. We propose the use of probabilistic downward counterfactual analysis to highlight and quantify the benefits of DRM interventions that otherwise remain invisible. This can serve to lift up the iterative, long-term, humble, dedicated and politically courageous actions required for long-term resilience building.

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